Proceedings of the 2013 Winter Simulation Conference
R. Pasupathy, S.-H. Kim, A. Tolk, R. Hill, and M. E. Kuhl, eds

HYBRIDIZED OPTIMIZATION APPROACHES TO THE SCHEDULING OF MULTI-PERIOD MIXED-BTU NATURAL GAS PRODUCTS

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ABSTRACT

Decisions regarding the buying, storing and selling of natural gas are difficult facing the high volatility of prices and uncertain demand. The increasing availability of low-Btu gas complicates decisions faced by investors and operational planners of consumers of natural gas. This study examines multiple approaches to maximizing profits by optimally scheduling the purchase and storage of two gas products of different energy densities and the sales of the same combined with a blended third product. Three approaches, a Branch and Bound-linear programming hybrid, a stochastic search algorithm-linear programming hybrid, and a pure random search are developed and tested in simulated environments. To make each technique computationally tractable, constraints on the units of product moved in each transaction are implemented. Using numerical data, the three approaches are tested, analyzed and compared statistically and graphically along with computer performance information. The result provides a basis for planners to improve decision making.

1 INTRODUCTION

Investors in natural gas seek to maximize profit by taking advantage of the seasonal low and high prices. Decisions regarding buying, storing and selling natural gas are difficult in the face of high variability of prices and uncertain demand. Various investment and management strategies exist. Operational planners for commercial and industrial consumers of natural gas use various techniques for planning the buying, storage and selling of the product.

This paper describes our approach of combining simulation and linear programming to optimize the decision process. While the focus is multi-cavern salt dome storage facilities, which have faster inventory turnover rates than the more common reservoir storage facilities, it is recognized that not all gas discussed in this paper is stored in such facilities (FERC 2004).

With economical stresses and increased emphasis on the protection of Earth's environment, the use of natural gas from alternate sources has increased. In many cases, such gas contains a lower energy content or Btu level, and while it may not be economically feasible to remove the impurities, it may still be desirable to use the gas rather than simply burning or 'flaring' it (EPA 2012). Further complicating the problem is that the price curves of gas from different sources may not be synchronized.

Consumers and investors seek a means of executing the planning process in the presence of gases of differing energy content levels. The primary purpose of this research is to acquire knowledge of techniques for optimizing the scheduling of buying, storage and selling of natural gas inventories of differing heat contents, specifically to maximize profits or minimize costs in these operations. Much work has been done in the area of scheduling standard pipeline-ready gas, but there exists a gap in the literature regarding mixed content gas. This problem has nuances that differentiate it from existing research on mixed-product problems. Further, the nature of natural gas and how it is stored distinguishes it from most commodities. For example, one distinctive characteristic of gas storage is that the rate of injection or delivery is related to the amount in storage at the time (Holland 2008).

The contribution this study makes in two areas lends to its significance. First, it adds to the research in this field by contribution to the study of mix-product natural gas scheduling. It provides initial information regarding the optimization of natural gas storage and scheduling, a logistical and financial problem that has been studied a long time and will continue to be investigated.

Secondly, it adds to the body of environmental studies work. Methane is the primary component of natural gas and is present in other bio-generated gases. It is considered to be a contributor to global warming and is seen as a pollutant when released into the atmosphere. As more and more low-Btu gas is captured to be used rather than released into the environment it is desirable to optimize its distribution and consumption.

Three common numerical approaches that are applied to the valuation of gas in storage: Monte Carlo simulation, numerical partial differential equation techniques and binomial/trinomial trees (Holland 2007). Stochastic optimization techniques find widespread use in simulation optimization. When modeling natural gas storage and scheduling, it is common to use a Monte Carlo process to simulate the forward price curve, (Blanco 2002; Bjerksund et al. 2011).

The practice of treating actual business opportunities as financial instruments is known as “real options theory.” Frayer and Uludere (2001) identify five key components of real options: value of asset, exercise or strike price, time to expiration, volatility and risk-free rate. They modify the Black-Scholes model to real options and use it to evaluate a power production facility (Black and Scholes 1973). Lai, et al. (2011) combined real option theory and stochastic-dynamic-programming to achieve a more tractable model for valuating liquid natural gas storage. Longstaff and Schwartz (2001) developed an approach to valuing American options through simulation using a least-squares approach. The framework of this approach was based on Black and Scholes’ work. Boogert and Jong (2008) adapted this approach to include complexities of natural gas storage, such as injection and withdrawal rates and working volume, and used Monte Carlo to model prices.

In the next section of this paper the problem will be defined. Section 3 describes the methodologies applies and the results are discussed in the fourth section. Finally, Section 5 presents conclusions and ideas for further investigation.

2 PROBLEM DEFINITION

Natural gas has a cyclical demand pattern-- low in the fall, high in the winter as temperatures drop, low again in the spring, and then slightly higher in the hotter months as the demand for electricity for cooling increases. To hedge against the cyclical demand pattern, gas is placed into underground storage. Investors and operators of gas-consuming facilities seek ways to optimize the decision to buy, sell or hold natural gas when there exist gases of different energy contents. Buyers of natural gas, whether as an investment tool or for consumption, seek to take economic advantage of the cyclical nature of gas prices, balancing seasonal cost differentials against storage costs. In this model, consumption is thought of as an exchange of gas for heat or energy and is viewed as a sale at the market spot buy price.

The heat content or heat of combustion is the energy released when a substance undergoes combustion with oxygen under standard conditions, 60ºF and 14.696 psia. This may be known as heat of combustion, heating value or calorific value. Units are expressed as heating value per unit mass or volume. British thermal unit (Btu) per cubic foot is a common measurement of natural gas (NIST 2010). This value is typically expressed in units or energy per unit mass, (which may be expressed as volume for gasses at standard conditions).

Natural gas, though mostly methane, contains other hydrocarbons such as ethane, propane, and butane or other impurities which may increase or, more likely, decrease the heat content. While the heat content may range from 500 to 1500 Btu/ft^3, most gas has a heat content value in the range of 900 to 1100 Btu/ft^3 and before being transported via the US interstate pipeline systems, gas must have a heat content of approximately 1030 Btu/ ft^3.

Typical natural gas contracts are normally written on a 12-month basis and gas is priced for delivery to the Henry Hub in Louisiana (Holland 2007). The price of gas obtained from other points on the interstate pipeline will be offset to reflect the transportation cost from the Henry Hub (NEB 2001).

The following notations are used throughout the paper. Given period i, define

C_A	Cost of Gas_A
C_{Ab}	Cost of Gas_{AB}
CAP_A	Max Facility Storage Capacity of Gas_A
CAP_B	Max Facility Storage Capacity of Gas_B
C_B	Cost of Gas_B
CS_A	Storage cost of Gas_A \$/unit/month
CS_{AB}	Storage cost of Gas_B \$/unit/month
H	Horizon – number of time periods
I_A	Max injection rate of Gas_A
I_B	Max injection rate of Gas_B
INV_A	Facility Current Inventory of Gas_A
INV_B	Facility Current Inventory of Gas_B
MDVa	Max deliverable volume Gas_A
MDVb	Max deliverable volume Gas_B
p_a	Profit Gas_A
p_{ab}	Profit Gas_{AB}
p_b	Profit Gas_B
P_A	Sales Price of Gas_A
P_{Ab}	Sales Price of Gas_{AB}
P_B	Sales Price of Gas_B
r_A	Ratio of Gas_A in $Gas_{AB\,(1-\,r_B)}$
r_B	Ratio of Gas_B in Gas_{AB} $(1-r_A)$
R_{ABi}	Calculated profit of Gas AB in period i
R_{Ai}	Calculated profit of Gas A in period i
R_{Bi}	Calculated profit of Gas B in period i
$dvol_a$	Change in volume of Gas_A one period
$dvol_{ab}$	Change in volume of Gas_{AB} one period
$dvol_b$	Change in volume of Gas_B one period
V_A	Volume of Gas_A Injected
V_B	Volume of Gas_B Injected
V_A	Volume of Gas_A Withdrawn
V_{AB}	Volume of Gas_{AB} Withdrawn
$VolMax_A$	Max leased storage capacity of Gas_A
$VolMax_{AB}$	Max leased storage capacity of Gas_B
W_A	Max withdrawal rate of Gas_A
W_{AB}	Max withdrawal rate of Gas_{AB}
W_B	Max withdrawal rate of Gas_B
Y_A	Number annual inventory turns for Gas_A
Y_B	Number annual inventory turns for Gas_B

When using linear programming to find the product mix, the objective function being solved is

$$max(p_a dvol_a + p_{ab} dvol_{ab} + p_b dvolb),$$

subject to:

$$dvol_a + percentAinAB*dvol_{ab} <= MDV_a$$
$$dvol_b + percentBinAB*dvol_{ab} <= MDV_b$$
$$dvol_a>=0,\ dvol_b>=0,\ dvol_{ab}>=0$$

where d is change in volume and p, the profit of that transaction.

Throughout this model, a first-in-first-out (FIFO) pricing scheme is used for calculating the cost of gas sold. C_x is a function of the initial cost of inventory and cost of storage.

Multiple constraints are applied. The first is that gas must be in inventory the same month it is sold. Since gas can be sold and bought simultaneously, passing through storage, as it were, the inventory need not be in place at the beginning of the period but at the end. The second constraint is that contracted capacity, CCAP, not be exceeded.

There may be situations in which gas of one or both types is in a stream delivered directly from its source rather than in storage. In these cases, the total storage is equal to the maximum deliverable volume, effectively making the entire inventory pass through each period. Landfill gas would be such an example.

One more constraint implements a feature common to many natural gas storage contracts, i.e., that gas still in storage at the end of the contracted period is forfeited, effectively creating a product with an increasingly short shelf life. Gas injected at the beginning of a contract has an effective life of twelve months, while gas injected into storage two months prior to the end of contract has a shelf life of only two months. The penalty for having gas in storage at the expiration point of the storage contract is the loss of that gas at the current market price, the "spot" price.

The following equation encompassed these constraints and calculates value as

$$\begin{aligned} value = max \sum_{i=1}^{h} ((dW_{a_i} p_{a_i}\, dvol_{a_i} - c_{a_i} dvol_{a_i} dI_{a_i}) + \\ (p_{ab_i} dvol_{ab_i} dW_{ab_i}) + \\ (dW_{b_i} p_{b_i} dvol_{b_i} - c_{b_i} dvol_{b_i} dI_{b_i}))) - \\ (Inv_a h * Spot_a + Inv_b h * Spot_b) \end{aligned}$$

where W_i and I_i are decision variables, taking a mutually exclusive value of 1 or 0, representing the decision to withdraw (sell) or inject (buy) gas, respectively.

3 METHODOLOGY

The research examined the use of simulation optimization techniques in combination with linear programming to make optimal scheduling decisions regarding holding times, product mix values, product injection and withdrawal schedules and transactional quantities. In addition to simplified test data designed to provide clear demonstrations of functionality and accuracy, we used price and cost data from past years as input for natural gas data and estimated landfill/low-Btu gas prices based on current trends and prices (EIA 2012).

3.1 System Configuration

We used the simulation package Awesim and modules written in Microsoft C++ to generate scenarios and in some cases used the linear programming package, LP_Solve 5.5 to provide the economical product mix and then evaluated the results. Using Awesim, each entity represented a potential path and contained all information required to define each period and to generate values for the next. This included all cost, price and inventory data as well as other parameters. The entity 'aged' through the time horizon, 12 months in most cases, changing value as different decisions were executed. At the end of the 12-period horizon, that value was compared to that of the best-valued decision path and replaced it if it was better.

3.2 Approaches

Three approaches were developed and compared. A Branch and Bound (B&B) algorithm combined with linear programming (LP), B&B-LP, was developed. This hybrid was implemented as a recursively created trinary decision tree with options to buy, hold or sell gas at each node. Heuristics were applied to limit the number of nodes per branch and thereby make the algorithm more computationally tractable.

An evolutionary stochastic search algorithm (SS-LP) in combination with LP was developed. This direct stochastic search algorithm implemented the same heuristics as the B&B-LP hybrid. Table 1 illustrates the progression from a fully direct approach to a fully stochastic one.

Finally, in order to compare the computational efficiency of the LP solver versus pure random search of the solution space, a Pure Random Search (PRS)-based approach (SS) was developed. This approach did not operate under the same bounds as the B&B-LP and SS-LP algorithms. It used more relaxed search criteria.

Table 1: Methodologies.

Approach	Select Decision	Select Product Mix
Branch & Bound – LP Hybrid	Direct	Direct
Stochastic Search – LP Hybrid	Random	Direct
Stochastic Search	Random	Random

3.3 Branch & Bound with LP

This type of scheduling problem, with decision points made across a finite horizon, lends itself nicely to a B&B solution, with each node representing a decision point. Decision points in the trinary tree were created at each period of the 12-month horizon, three being generated from the previous node. While B&B is conceptually simple, it is not without its limitations. Although it can produce an exact optimum, with larger problems the amount of computer time required to find that solution may be too great to be useful. Without careful pruning, the number of bud nodes on a tree increases exponentially. Mousavi et al. (2012) found this to be true, that the performance of B&B compared to a genetic or simulated annealing algorithm, which produced *near*-optimal solutions, was significantly poorer.

This multi-item, product-mix, multi-period inventory problem is non-deterministic polynomial time, NP-Hard, and finding the solution is computationally infeasible. It cannot be solved efficiently as is, but it can be approached by reducing it to a simpler problem through the application of heuristics and bounds. A result of this problem restatement is that an approach that provides a near-optimal solution must suffice.

Algorithm 1: Branch and Bound Optimization with LP

```
for each entity loop
    initialize independent variables & parameters
    load prices, costs
    apply variance process to price and cost data (simulate market)
    (AWESim entity) enter B&B subroutine
    repeat while at least one entity is in the B&B subroutine
        case action: 'hold'
            if current inventory<periods remaining * transaction volume
                then apply action
            else prune branch
            end if
```

```
        case action: 'buy'
            if current inventory<periods remaining * transaction volume
                and current inventory + purchase <= max storage capacity
                then apply action
            else prune branch
            end if
        case action: 'sell'
            if current inventory or A and B
                then invoke LP_Solver
      apply results to value and inventory levels
            else process individual sale
            end if
        end case

        update status of entity
        if current entity is horizon (n)
            compare value to current best value
            if current value > best values
                swap values
            end if
        else spawn new entity for each action (buy,hold,sell)
               (entity) enter B&B subroutine
        end if
  end repeat
end loop
```

By selecting an action to be taken at a specific time, B&B identified a subregion of the solution set. That subregion was further searched by the LP routine to find the best combination of products to sell.

3.4 Stochastic Search with LP

In the second approach, the use of a stochastic search (SS) routine to select sub-regions from the solution set replaced the B&B algorithm. The decision to buy, sell or hold was then selected from a uniform random distribution with each decision receiving equal weight, i.e., there was no bias toward either of the three decision actions. Like the first approach, though, this one also used LP to optimize that selection.

Algorithm 2: Stochastic Selection with LP

```
for each entity (trial)
   initialize independent variables & parameters
   load prices, costs
   apply variance process to price and cost data
   (entity) enter SS-LP subroutine
   repeat for each iteration
      repeat for s=1 to max solution samples
         repeat for n=1 to horizon
            generate action (stochastic process)
            case action: 'hold'
               if current inventory<periods remaining * transaction volume
               then apply action
               else prune branch
   case action: 'buy'
               if current inventory<periods remaining * transaction volume
                  and current inventory + purchase <= max storage capacity
               then apply action
               else prune branch
```

```
   case action: 'sell'
      if current inventory or A and B>
      then invoke LP_Solve
      apply results to value and inventory levels
      else process individual sale
   end case
   if value of plan > best plan
   then set best plan=current plan
   end repeat
       end repeat
   end repeat
end loop
```

3.5 Stochastic Search

The stochastic search routine alone was used as the third method. Full-horizon decision paths were generated and evaluated based on random selections from the solution set, with the best result being tracked. Rather than using LP, the volume moved in each transaction was the result of a random process.

Algorithm 3: Stochastic Selection (SS)

```
for each entity (trial)
   initialize independent variables & parameters
   load prices, costs
   apply variance process to price and cost data
   (entity) enter SS subroutine
   repeat for s=1 to max solution samples
      repeat for n=1 to horizon
         generate inventory delta gas A   -100 (sell) to 100 (buy)
         % (in units of 25%)
         generate inventory delta gas B   -100 (sell) to 100 (buy) %
         generate inventory delta gas AB   -100 (sell) to 0%
         case action: 'buy'
            update entity inventory, value
         case action: 'sell'
            update entity inventory, value
         end case
         if value of plan > best plan
            then set best plan=current plan
      end repeat
   end repeat
end loop
```

Random Search (RS) or Pure Random Search (PRS) can be used and works on an infinite parameter space when it is not possible to evaluate every possible solution. This is the general case of random solution searches, being performed without any heuristics or rules for reducing the set of solutions. The process ends after a predetermined number of searches have been completed, a limit of computer resources has been reached or an acceptable solution has been found. This process performs best when a neighborhood can be defined in the solution space (Olafsson and Kim 2002). PRS has the advantage of avoiding local maxima. While it has been applied primarily to discrete problems, its closely related technique, sample path optimization, is practiced on continuous problems (April et al. 2003). While it can be shown that RS will converge to a near-optimal solution (Shi et al. 2000), one problem with this approach is the slow speed at which convergence is reached (Tekin and Sabuncouglu 2004).

The existence of other, more guided approaches notwithstanding, this approach does find use in practice. Poland, et al. (2011) applied a PRS algorithm to a smart home sensor placement problem and found that in 98.4% of test cases this approach produced superior results.

4 RESULTS

The B&B-LP algorithm provided, not surprisingly, the most accurate results. Within the constraints placed on it, the process enumerated and evaluated each possible path in the 12-period horizon. In 25 trials, the correct solution was found each time. The number of samples evaluated was based on the *maximum* number of candidate paths enumerated by the trinomial tree, $3^{12} = 531{,}441$. With the bounds placed on the algorithm, and considering the samples per second evaluated by the other approaches, it is unlikely that the solution set was fully enumerated. These results are shown graphically in Figure 1.

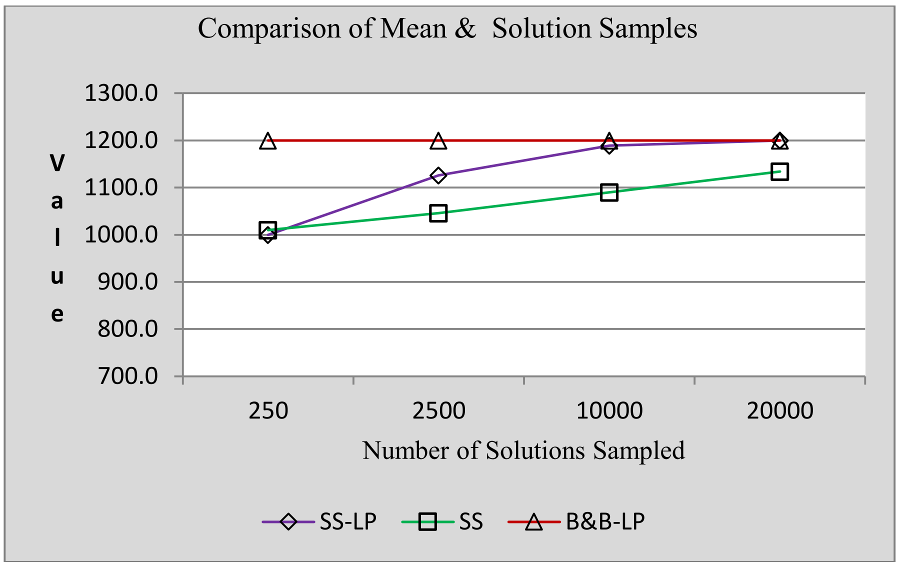

Figure 1: Best Solution Per Approach and Sample Size.

The SS-LP hybrid performed best when sampling 20000 solutions per iteration. It consistently found the optimum solutions with a STDDEV of 0.0.

The SS algorithm was created with the option of generating specific volumes of gas to be bought or sold, with a range from -100% to 100% of the maximum transfer amount, and was initially generated in 25% increments. In practice, it turned out that this expanded the solution space to the point that the SS approach could not reliably converge to a near-optimal solution in a reasonable time. Figure 2 graphically compares the accuracy and rate of convergence with that of the baseline, B&B-LP.

The Branch & Bound-LP hybrid was the best of the three approaches used in this project. It returned the optimal solution and, when compared to the SS-LP and SS algorithms that actually executed long enough to generate a reliable optimum or near-optimum solution, it was the least computationally expensive.

5 CONCLUSIONS AND FUTURE RESEARCH

This project has sought to extend current research by examining methods of optimizing the decisions that are made by gas investors and facility operators. The specific focus was the combination of gases of different energy contents, or Btu levels. This topic grows in importance as businesses seek to optimize resources and as environment pressures dictate the consumption of gas of lesser quality.

Simulation optimization is commonly employed to solve or find reasonable solutions to problems such as this. Gas market environment was simulated using Monte Carlo techniques and three approaches were used to optimize profit in that market.

The B&B-LP hybrid was, within the constraints of the program, the most accurate, always returning an optimal solution and in the best time. This accuracy was generated at the expense of flexibility and perhaps oversimplification. Heuristics were applied to reduce the number of decision points at each node, exponential growth being the nemesis of dynamic programming.

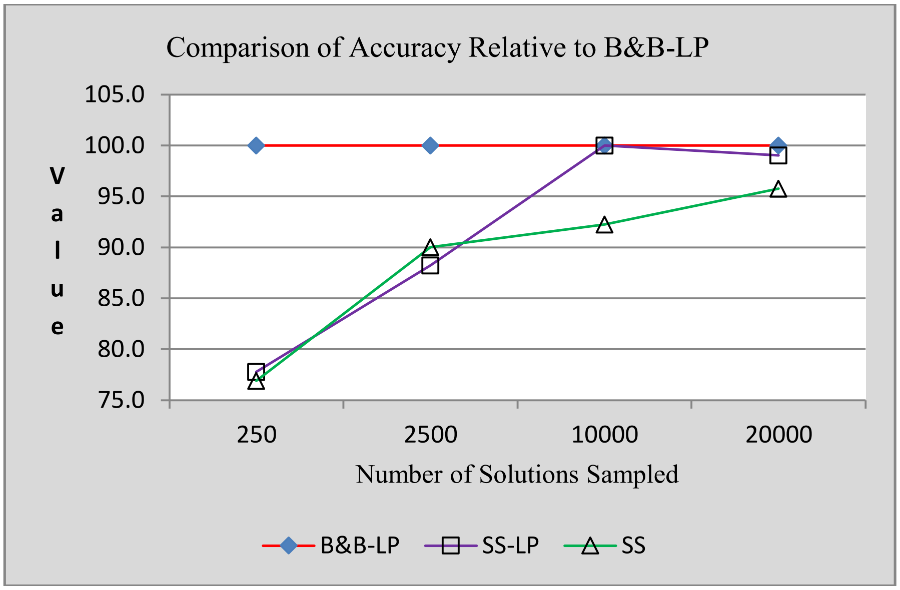

Figure 2: Accuracy of Non-Branch and Bound Approaches.

The advantage of the Stochastic Selection-Linear Programming (SS-LP) algorithms was its flexibility. It was not as efficient computationally as the B&B-LP approach, but it was more readily modified to new constraints. While the simplest and most flexible approach, the generic Stochastic Selection (SS) algorithm proved to be too computationally expensive to use without some constraints. For example, percentage of shipping volumes were selected from a set of three options, -100%, 0, and +100%.

Quality of Solution Conclusions. Each of the three algorithms produced optimal solutions in both test cases. The B&B-LP model found the optimal solution in the shortest time. Not surprisingly, the accuracy of the stochastic solution search routines was directly proportional to the number of sample solutions examined. The SS–LP model provided the optimal solution with a STDEV of 0.0 when 20,000 solutions were examined. The SS model exhibited the same performance.

The energy industry and natural gas in particular is a global concern and, as it faces changes from economic, technological and environmental stimuli, there will be new and important areas of research. This project has examined and offered an useable approach, an approach superior to one based solely on historical performance, to a problem that has become more prominent in the industry and will continue to receive attention.

One enhancement to the model might be to include the present value of money (PVM), in the cost function. The inclusion of futures prices and the introduction of a geometric Brownian motion function to the price variable module may also prove profitable.

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